Evaluation Method of College Students' Learning Autonomy Based on Social Network Support

https://doi.org/10.3991/ijet.v18i10.40237

Runfang Duan[1], Xiaorui He[2](✉)
[1]Department of Student Affairs, Liuzhou Institute of Technology, Liuzhou, China
[2]Department of Student Affairs, Beijing College of Social Administration, Beijing, China
hexiaorui@bcsa.edu.cn

Abstract—Social network plays an important role in college students' life. The greater the social network support they have, the more adequate social network resources they get, and the stronger their ability to cope with the challenges of study and life is. Existing studies have overemphasized the influence of social environment on college students' academic success, and have not paid special attention to the influence of the outside world on the change of college students' learning attitude. Therefore, this article studies the evaluation method of college students' learning autonomy based on social network support. Firstly, the local and global features of network nodes are extracted, and the social network roles of college students are divided. Then, a new logical structure network is constructed based on the vector representation of each node, which maximizes the influence of relevant nodes on college students' social network support. Finally, based on the new network structure, the meta-path walking algorithm is introduced to evaluate college students' learning autonomy by obtaining the attribute features supported by social networks through network nodes. Experimental results verify the effectiveness of the proposed method.

Keywords—social network, social network support for college students, learning autonomy

1 Introduction

Social network plays an important role in college students' life. It has become a part of college students' life, and has an incalculable influence on college students' information acquisition, thinking, learning and life [1–5]. Social network serves a window for college students to obtain information, show themselves and improve themselves [6–9]. College students are eager to succeed in their studies and life, but there are many complicated factors that affect their success, especially the social network support they have [10–13]. The greater the social network support they have, the more adequate social network resources they get, and the stronger their ability to cope with the challenges of study and life is. Existing studies have discussed how to provide necessary help to college students with insufficient social network resources, ignoring the influence of social network support on their academic success [14–20]. Learning autonomy represents the degree to which students actively adjust their learning strategies and efforts based on existing support conditions. It is necessary to study the evaluation method of college students' learning autonomy based on social network support.

Fernández-Vera et al. [21] puts forward two studies, focusing on two research questions: (1) How do college students in southern Chile communicate? (2) Can mobile apps persuade college students to increase their communication patterns? To answer these questions, the document conducts a survey of 90 students in southern Chile, and then develops a persuasive app called Social + Me, designed to monitor communication with student support networks and persuade them to stay in touch. Previous studies have shown that learners' autonomy depends on the role of teachers. Huang [22] aims to explore the ideal and reality of college English teachers' promotion of learners' autonomy in blended learning classrooms. Quantitative research method is adopted. Two Likert questionnaires are conducted among 100 undergraduates. The collected data is processed in SPSS 25.0. The results show that teachers' practices are mostly inconsistent with students' expectations, which shows that teachers fail to meet students' needs. It is suggested to cultivate students' autonomy in blended learning environment. The purpose of Aziz et al. [23] is to emphasize the use of technology to improve learning autonomy in EL classrooms. At the same time, it enables learners to fully control their own learning process, so as to better understand the materials they have learned and learn EL. This article will study the use of technology to promote learners' autonomy in EL classroom, drawing on the new technology practice in educational research and teaching process. Student-centered learning requires students to be responsible for their own learning and become autonomous learners. Duarte [24] reports some research results of Portuguese mechanical engineering students' learning autonomy (the first cycle) using hybrid method and sequential interpretation design. In this article, the focus is on the relationship between learners' autonomy and academic achievement, and how it translates into students' views on learning autonomy, its features and importance, and the ways of learners' autonomy improving their learning and build a bridge between research and practice in engineering education. The results show that students have positive views on their learning autonomy and its importance.

Existing studies overemphasize the influence of social environment on college students' academic success, and do not pay special attention to the influence of the outside world on the change of college students' learning attitude. At the same time, the role of college students in social network is simply defined as negative and passive, ignoring the influence of college students' personal initiative behavior on themselves and social network. Therefore, it is necessary to adopt subjective, objective, qualitative and quantitative methods to evaluate college students' learning autonomy based on social network support, which can ensure the accuracy and rationality of the research results. Therefore, this article studies the evaluation method of college students' learning autonomy based on social network support. Firstly, in the second chapter 2, the local and global features of network nodes are extracted, and the social network roles of college students are divided. The third chapter constructs a new logical structure network based on the vector representation of each node, which maximizes the influence of relevant nodes on college students' social network support. The fourth chapter introduces meta-path walking algorithm on the basis of the new network structure, and evaluates college students' learning autonomy by obtaining the attribute features supported by social networks through network nodes. Experimental results verify the effectiveness of the proposed method.

2 Division of college students' social network roles

According to the role features of network nodes in college students' social support network, they can be divided into three categories: direct support nodes, indirect support nodes and ordinary nodes. The goal of this article is to design a feasible solution to classify and define the roles of social support network nodes for college students through the feature attributes of network nodes.

In order to identify the direct support node s in the network, this article analyzes the influence of each node based on the extraction of local and global features of the network nodes. The local influence of Node *i* on Node *j* is influenced by Node *i* itself and the number of common friends of Nodes *i* and *j*. These two influences are usually determined by the degree of nodes and the number of common friends in social networks. Assuming that the local influence of Node *i* on Node *j* is represented by *LI*, the probability of information propagating from Node *i* to its one-hop neighbor node is represented by *C*(*i*), and the direct neighbor node of Node *i* is represented by *Q*(*i*), this article introduces equilibrium parameters β_1 and β_2 to quantify the local influence of network nodes of college students' social support network:

$$LI_{ij} = \beta_1 C(i) + \beta_2 \frac{|Q(i) \cap Q(j)|}{|Q(i) \cup Q(j)|} \tag{1}$$

In the above formula, β_1 and β_2 satisfy $\beta_1 + \beta_2 = 1$. The local influence value of Node *i* is the average of the local influence of *i* on all its neighbors. Assuming that the neighborhood node set of Node *i* is represented by *M*(*i*), then:

$$LI_i = \frac{1}{|M(i)|} \sum_{j \in M(i)} LI_{ij} \tag{2}$$

Assuming that the shortest number of paths between two Nodes *j* and *l* is represented by T_{jl}, and the shortest number of paths with *l* through Node *i* is represented by T_{ijl}, the mediation centrality index value can be calculated based on the local influence of *i*:

$$Y(i) = \sum_{i,l,j \in U, i \neq j \neq l} \frac{T_{jil}}{T_{jl}} \tag{3}$$

The final influence of Node *i*, that's, the social network support provided to college students, can be the sum of the global and local structural information of Node *i*. The final influence of Node *i* represents the possibility and key of becoming the direct support node of college students' social network. Assuming that the direct support influence score of Node i is represented by $W(i)$. The equilibrium parameters for adjusting the global and local influence ratio of nodes are expressed by γ_1 and γ_2, then:

$$W(i) = \gamma_1 LI_i + \gamma_2 Y(i) \tag{4}$$

In the above formula, γ_1 and γ_2 satisfy $\gamma_1 + \gamma_2 = 1$.

There are nodes spanning multiple social support sub-networks in college students' social support network, which promote the information exchange among social support sub-networks and can be regarded as structural hole nodes of the network. According to the complex network theory, the smaller the network constraint coefficient of college students' social support network is, the more structural hole nodes may be, and the greater the possibility of network structure hole is. Assuming that the network constraint coefficient value of Node i is represented by $MD(i)$, and the proportion of the input of Node i to maintain the relationship with j to the total input is represented by η_{ij}, then:

$$MD(i) = \sum_{j \in Nei(i)} \left(\eta_{ij} + \sum_{l \in Nei(i)} \eta_{il}\eta_{lj} \right)^2, (i, j, l \in U, l \neq i, j) \tag{5}$$

The first k smaller nodes in the calculation results of the network constraint coefficient $MD(i)$ are selected and determined as indirect support nodes of the social support network for college students.

The selection threshold of direct support and indirect support nodes in college students' social support network is used to adjust the proportion of the two types of nodes, which are represented by α_1 and α_2. Assuming that the set of ordinary nodes is represented by E_s, the set of direct support nodes is represented by E_t, the set of indirect support nodes is represented by R_p, and all node sets of social support network are represented by U, the following formula can give the expression of node set of ordinary network nodes in the network:

$$Es = U - Et - Rp, (|Et| = |U| * \alpha_1, |Rp| = |U| * \alpha_2) \tag{6}$$

3 Maximizing the influence of college students' social network support

Based on the second chapter, it's possible to get the representation of all nodes in the social support network of college students: $\Omega \in S^{|U| \times c}$. Because the larger the cosine similarity value of the vector represented by two nodes is, the greater the probability of mutual influence between the two nodes is. In order to make college students get the most social network support, this article constructs a new logical structure network based on the vector representation of each node. The schematic diagram of the realization process of maximizing the influence of social network support for college students is given in Figure 1. The new network constructed represents the influence probability relationship among network nodes, which can be defined as propagation probability network. In order to construct a new network structure, this article sets a similarity threshold ω to judge whether logical connection edges are added to the new network structure, which satisfies $\omega \in (0,1)$. The following formula gives the calculation formula of connection edge strength between any two nodes in the new network structure:

$$t_{i,j} = \begin{cases} UH(i,j), if \quad UH(i,j) \geq \omega \\ 0, otherwise \end{cases} \tag{7}$$

Assuming that the hyperparameter is represented by ω and satisfies $\omega \in (0,1)$. The information propagation probability from Node i to Node j in the network can be characterized by the above formulas $t_{i,j}$. By default, the influence probabilities between network nodes are independent of each other. Based on the propagation probability of neighbor nodes of Node i, the probability that the node is activated by its neighbor node $FA(i)$ for social network support for college students can be calculated:

$$Ts(U \mid i) = 1 - \prod_{j \in FA(i)} (1 - t_{i,j}) \tag{8}$$

Similarly, for each node $j \in U$, under the influence of the node set R that has provided social support, the total activation probability of all nodes that have not provided social support can be calculated by the following formula:

$$xTs\ (U \mid R) = \frac{1}{|U|} \sum_{i \in U} \left[1 - \prod_{j \in FA(i)} (1 - t_{i,j}) \right] = 1 - \frac{1}{|U|} \sum_{i \in U} \prod_{j \in FA(i)} (1 - t_{i,j}) \tag{9}$$

In the task of maximizing the influence of social network support, the ultimate goal of the constructed model is to activate more nodes that do not provide social support under the influence of R, in other words, to make the expectation $Ts(U|R)$ larger. The following formula gives the model optimization goal expression at this time:

$$\begin{aligned} \arg\max_R &= \arg\max_R 1 - \frac{1}{|U|} \sum_{i \in U} \prod_{j \in FA(i)} (1 - t_{i,j}) \\ &= \arg\min_R \frac{1}{|U|} \sum_{i \in U} \prod_{j \in FA(i)} (1 - t_{i,j}) \end{aligned} \tag{10}$$

Because the model objective shown in the above formula cannot be optimized directly, this article chooses heuristic algorithm to solve it, so as to realize the effective selection of node set R that has provided social support.

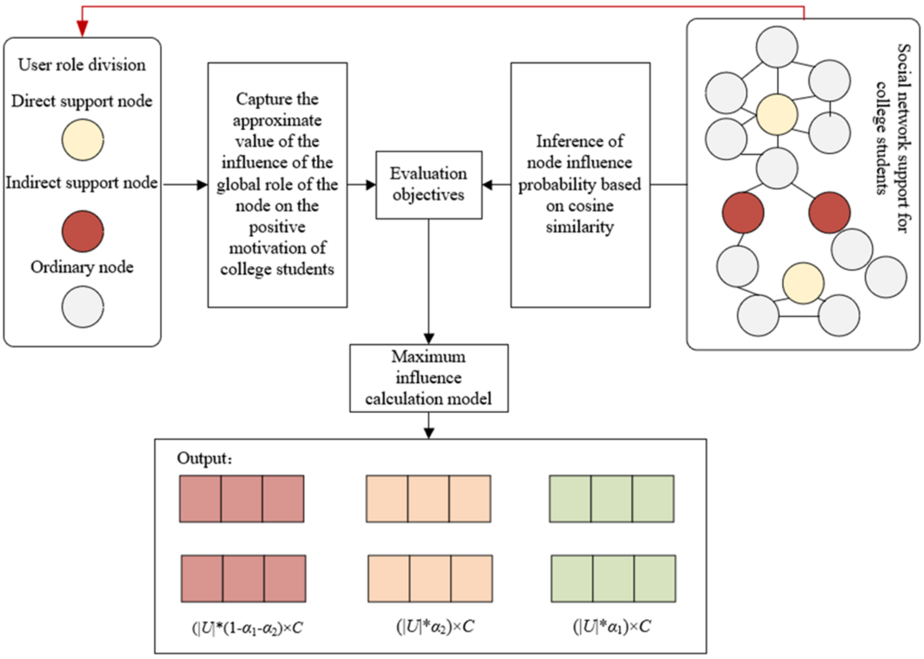

Fig. 1. Schematic diagram of the realization process of maximizing the influence of social network support for college students

4 Evaluation of learning autonomy based on meta-path walking

In the previous chapter, it's possible to get a perfect new network structure by dividing the roles of network nodes, inferring the influence probability relationship and determining the maximum influence goal in the social support network for college students. According to the general process of network node attribute inference of social support network for college students, the embedding features of network nodes can be further obtained based on the embedding model, and the network node attribute inference based on the ensemble learning model can be realized at the same time. This article evaluates college students' learning autonomy by obtaining the attribute features of social network support from network nodes. However, the node feature vectors obtained by statistical analysis or embedding model are not enough to characterize the influence of network nodes on college students' learning autonomy. Therefore, on the basis of the new network structure, this article introduces meta-path walking algorithm, and characterizes the positive incentive influence of social network support on college students' academic success through the multi-dimensional walking features of network nodes, that's, the promotion of college students' learning autonomy.

The meta-path in the new network structure is defined as the sequential relationship between two node role types. Assuming that the meta-path in the new network structure is represented by T, the meta-nodes are represented by u_1, u_2 … $u_{k+1} \subseteq US$, and the influence probability meta-relationship is represented by O_1, O_2 … $O_k \subseteq O$, the following formula gives a meta-path expression with a length of 1 from node role type u_1 to node role type u_{k+1}:

$$T = u_1 \xrightarrow{O_1} u_2 \ldots \xrightarrow{O_k} u_{k+1} \tag{11}$$

Specific to the new network structure of college students' learning autonomy inference in this article, meta-nodes and meta-relationship can be redefined. For meta-nodes, the nodes can be divided into direct support nodes and indirect support nodes with positive incentive and ordinary nodes without incentive according to the results of node role determination during the construction of the new network structure. It is difficult to judge the nature of the influence probability relationship because of the complex types of relationships between meta-nodes. In order to solve this problem, based on the link embedding features of the new network structure and Kmeans clustering algorithm, this article obtains the best classification of node relationship for the incentive influence of college students' learning success. The specific acquisition steps are described as follows:

1) Based on the new network structure embedding model, the embedding representation of the influence probability relationship of all nodes is calculated.
2) Set the threshold value P, adjust the number of clustering algorithms in the range of $[1, P]$, and perform P-times clustering operation on the embedding representation of node influence probability relationship facing the influence of college students' learning success incentive.
3) The obtained P different clustering results are evaluated based on Calinski-Harabasz scores. Assuming that the number of training set samples is represented by a, the number of clustering clusters is represented by l, the covariance matrix between categories is represented by Y_1, the covariance matrix of data within categories is represented by Q_1, and the trace of the matrix is represented by $tr(\cdot)$, then:

$$CH(l) = \frac{tr(Y_l)}{tr(Q_l)} \frac{a-l}{l-1} \tag{12}$$

When the calculation result of the above formula is the largest, the number of categories of the corresponding meta-relationship is the best. Based on the redefinition of meta-path, it's possible to design a meta-path for inferring college students' learning autonomy. Considering that the subject body of college students' learning autonomy evaluation task is college students, and the starting node and ending node of meta-path are both college students' nodes, the designed meta-path needs to meet the bounded length less than or equal to 3.

It is assumed that l' new network structure meta-paths are obtained after the previous analysis. Next, this article takes these meta-paths as constraints to infer the influence tendency attributes of college students' learning autonomy in network nodes. The identification of the influence tendency of college students' learning autonomy in network nodes based on meta-path walking is mainly divided into two stages: meta-path feature extraction, and network node representation and inference. The specific contents of the two stages are introduced below.

For convenience of expression, it is assumed that the left endpoint set of meta-relationship O_1 is represented by $XC(O_1)$, the left endpoint set of meta-path T is represented by $XC(T)$, the right endpoint set of meta-relationship O_1 is represented by $XZ(O_1)$, and the right endpoint set of meta-path T is represented by $XZ(T)$. Assuming that there is a meta-path $T=u_1 \rightarrow^{O1} u_2 \ldots \rightarrow^{O2} u_{k+1}$, then starting from the query node set $u_w \subseteq XC(T)$, according to the rules of meta-path T, the influence tendency attribute features of any node x in $XZ(T)$ on college students' learning autonomy can be expressed by $f_{uw,T}(x)$, which can be calculated by the following formula when the length of T is 0:

$$f_{u_w,T}(x) = \begin{cases} \frac{1}{|u_w|}, if \quad x \in u_w \\ 0, others \end{cases} \tag{13}$$

When the length of T is greater than 0, $XZ(T)$ needs to be eliminated, and the meta-path is $T' = u_1 \rightarrow^{O1} u_2 \ldots \rightarrow^{Ok-1} f_{uw,T}(x)$. Assuming that the activation function is represented by $HS(\cdot)$, $f_{uw,T}(x)$ can be calculated by the following formula:

$$f_{u_w,T}(x) = \sum_{x' \in XZ(T')} f_{u_w,T'}(x') \cdot \frac{HS\left(O_k(x',x)\right)}{\left|O_k(x')\right|} \tag{14}$$

It can be seen from the above formula that $HS(O_k(x', x))$ is 1 if $O_k(x', x)$ is true; otherwise $HS(O_k(x', x))$ is 0 if $O_k(x', x)$ is false. Through the above process, get the eigenvalues $f_{uw,T}(x)$ of college students' learning autonomy influence tendency attribute from $u_w \subseteq XC(T)$ to any node x in $XZ(T)$ with regular load element path T.

From the above calculation results, it can be seen that in the process of solving $f_{uw,T}(x)$, firstly, the known direct support nodes and indirect support nodes with positive incentives for college students' learning autonomy will be selected from the network nodes of the new network structure as the query node set $u_w^+ \subseteq XC(T)$, and the ordinary nodes $u_w^- \subseteq XC(T)$ without incentives will be eliminated. After solving the eigenvalue $f_{uw,T}(x)$ of any node x in u_w, taking the known u_w^+ as the starting point, according to the order of meta-path T = college student node $\rightarrow^{\text{supporting relationship/supported relationship}}$ support node $\rightarrow^{\text{sending}}$ neighbor ordinary node $\rightarrow^{\text{sent}}$ college student node, $f_{uw+,T}(x)$ can be further solved based on Formula 14, that's, the eigenvalues of college students' learning autonomy influence tendency attribute under meta-path T from u_w^+ for all network nodes. The detailed process is shown in Figure 2.

Based on meta-path walking network node, college students' learning autonomy influence tendency identification algorithm flow will traverse all meta-paths. Firstly, for each meta-path T_i, the $f_{uw,T}(x)$ value of any node x in the non-starting node set is calculated until the college student node set of T_i is calculated, and the feature matrix F_j of the college student node set of T_i can be obtained. Repeating the above calculation process on all meta-paths can obtain the feature matrix F of college students' node set on all meta-paths, and taking the transposed F^T of F as the input of the evaluation model of college students' learning autonomy, the inference result vector of college students' learning autonomy influence tendency of all network nodes can be obtained.

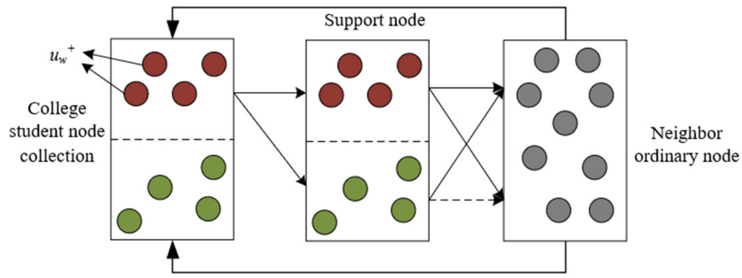

Fig. 2. Schematic diagram of the process of identifying the influence tendency of college students' learning autonomy

5 Experimental results and analysis

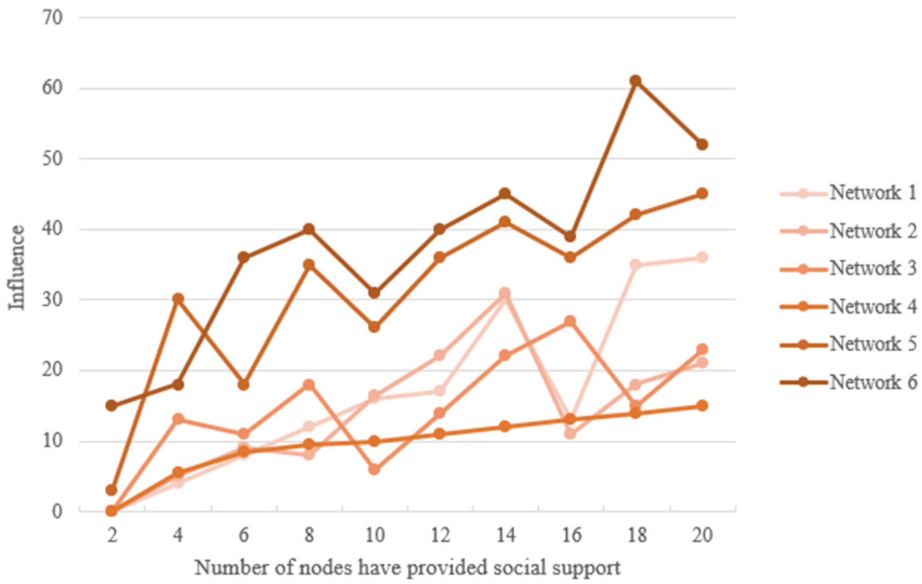

Fig. 3. Comparison of simulation results of six different networks

In this chapter, firstly, a comparative experiment on the influence scope of college students' social network support under different node sets *R* scale that have provided social support is carried out. Figure 3 shows the simulation results of node influence corresponding to six networks with different *R*-scale conditions. It can be seen from the figure that the influence range of all network nodes on college students' social network support increases with the increase of *R* scale. When the *R* scale is smaller, the influence range of six different *R* scale networks on college students' social network support is close. With the increase of *R* scale, the constructed network model can still better characterize the influence probability relationship between network nodes, which shows obvious advantages in realizing the task of maximizing the influence of social network support for college students, and lays a foundation for further evaluation of students' learning autonomy.

It is worth noting that due to the different scales of the node set *R* scale that have provided social support, the scale of the query node set for identifying the influence tendency of college students' learning autonomy in the experiment is also different. For example, in Network 1 with a query node set size of 40, a set of nodes having provided social support of up to 20 nodes is constructed. In Network 2 with a query node set size of 450, a set of nodes having provided social support of up to 200 nodes is constructed. In order to evaluate the efficiency of the proposed method in maximizing the influence of social network support for college students, Table 1 summarizes the average simulation results of six different networks under different balance parameter selection. This table gives the average of the influence range of network nodes on college students' social network support based on 18 experiments with different balance parameters. It can be seen from the table that the proposed method can obtain the best experimental results when the balance parameter is 0.4, especially for network 4 and network 6.

Formula 7 introduces the similarity threshold ω, which is used to judge whether to add logical connection edges to the new network structure, to construct a new network which represents the influence probability relationship between network nodes. The value of this parameter will directly affect the accuracy of simulation results, so this article analyzes the value of this parameter. Similarly, considering the size of the node set *R* that has provided social support, this article sets different step sizes. Figure 4 shows the comparison of simulation results with different similarity thresholds ω. It can be seen from the figure that the similarity threshold ω has certain influence on the experimental results under the same *R* scale, but the influence degree of ω on the experimental results is different under different *R* scales. Because this article takes into account the influence of *R* scale nodes on the scope of social network support for college students, so this article further counts the different ω settings for different network sample sets and set the optimal ω value of different network sample sets.

After the construction of the new network structure, in order to verify the effectiveness of the proposed evaluation method of college students' learning autonomy based on meta-path walking, this article explores the influence weights of all meta-path nodes involved in the new network structure in the inference of college students' learning autonomy influence tendency, and the results are shown in Figure 5. It can be seen from the figure that the influence weights of nodes involved in the same meta-path are different when the positive incentive node set is used as the query node set and the non-incentive node set is used as the query node set, which shows that these nodes provide different social support to college students. This phenomenon also shows that there are some differences in the meta-path construction models between the node sets with positive incentives and the node sets without incentives for college students' learning autonomy.

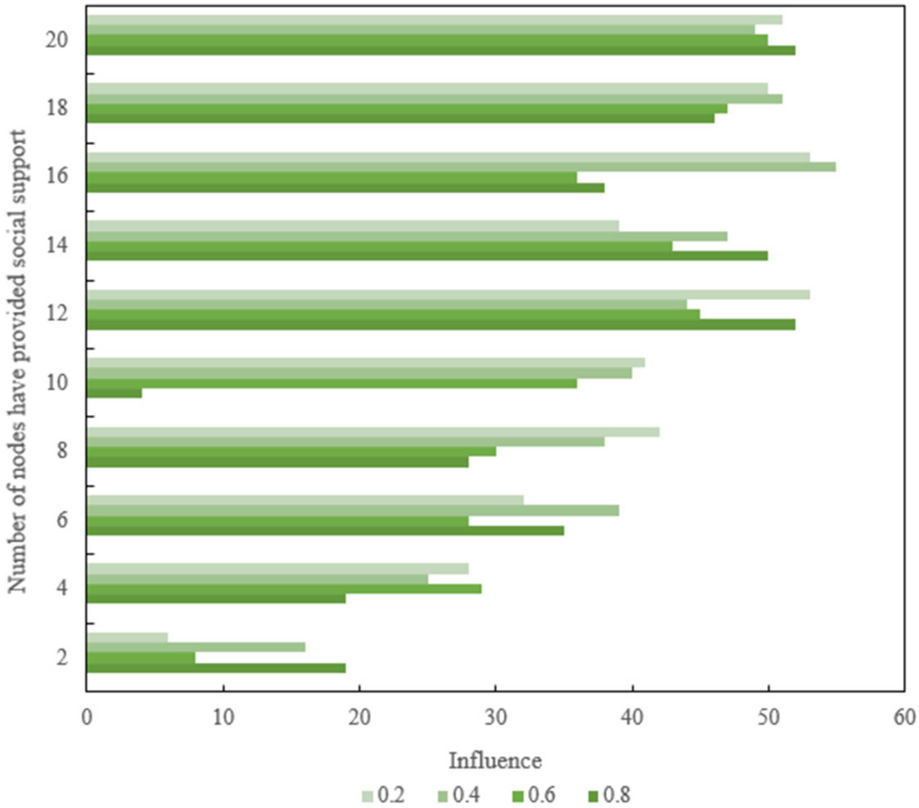

Fig. 4. Comparison of simulation results with different similarity thresholds ω

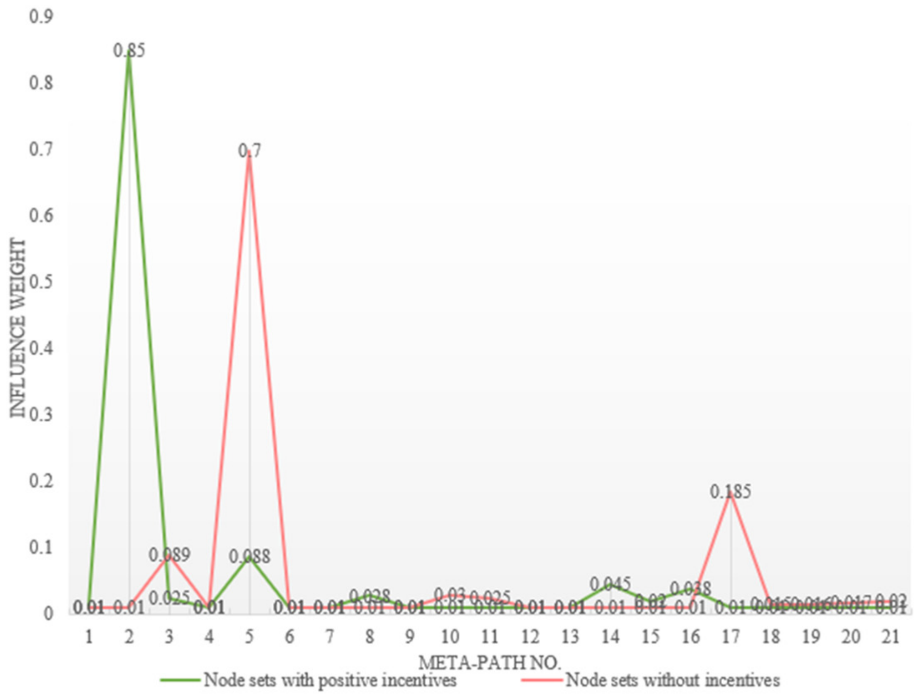

Fig. 5. Weight of node influence in the evaluation of college students' learning autonomy

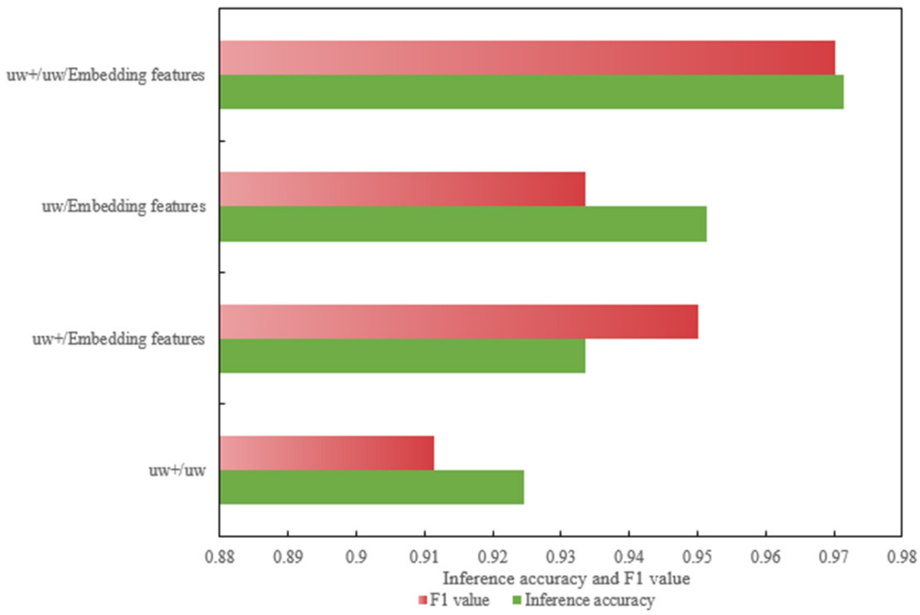

Fig. 6. The influence of feature integration on the evaluation performance of college students' learning autonomy

Table 1. Comparison of experimental results of different equilibrium parameters selected on six different networks

	0.1	0.2	0.3	0.4	0.5	0.6
Network 1	12.5	15.9	11.2	35.2	32.4	13.5
Network 2	23.8	42.5	236.1	417.1	326.1	162.9
Network 3	112.4	152.6	147.9	436.9	304.7	135.2
Network 4	106.9	136.9	253.1	925.1	629.5	149.5
Network 5	85.3	157.2	285.4	641.7	614.1	131.2
Network 6	214.2	325.6	417.3	2514.2	1528.6	269.5

Next, this article further explores the influence of meta-path walking feature integration on the evaluation performance of college students' learning autonomy. This experiment is a comparative experiment of four groups of feature integration methods. In the first group, it is designed to splice and integrate the walking features of u_w^+ and u_w^- departure calculation; in the second group, it is designed to splice and integrate the walking features of u_w^+ departure calculation and the embedding features of the influence probability relationship of all nodes; in the third group, it is designed to splice and integrate the walking features and embedding features of u_w^- departure calculation; in the fourth group, it is designed to splice and integrate the walking features and embedding features calculated by u_w^+ and u_w^-. The experimental results are shown in Figure 6. It can be seen from the figure that after the completion of feature integration, compared with the two feature integration, the three feature integration can obtain more ideal evaluation accuracy and F1 value in the evaluation task of college students' learning autonomy, which proves that feature integration has a positive effect on the evaluation performance of college students' learning autonomy. At the same time, it's also possible to find that the walking feature of u_w^+ departure calculation has a more significant dominant position. Moreover, the integration of the embedding features of the influence probability relationship of all nodes will obtain better performance evaluation results, which verifies that the embedding features representing the global information of the network complement the information not contained in the meta-path walking features representing the detailed features of the network. Therefore, the integration of the two will achieve better results in the evaluation of college students' learning autonomy.

6 Conclusion

This article studies the evaluation method of college students' learning autonomy based on social network support. Firstly, the local and global features of network nodes are extracted, and the social network roles of college students are divided. Then, a new logical structure network is constructed based on the vector representation of each node, which maximizes the influence of relevant nodes on college students' social network support. Finally, based on the new network structure, the meta-path walking algorithm is introduced to evaluate college students' learning autonomy by obtaining the attribute features supported by social networks through network nodes. Combined with experiments, the influence simulation results of nodes corresponding to six different R scale networks are given, and verify that the constructed network model can better characterize the influence probability relationship among network nodes. The experimental results of different balance parameters and similarity threshold ω on six different networks are compared, and an ideal new network structure is constructed. The influence weights of nodes in the evaluation of college students' learning autonomy are given, and the influence of feature integration on the evaluation performance of college students' learning autonomy is discussed to verify the effectiveness of the proposed evaluation method of college students' learning autonomy based on meta-path walking.

7 Acknowledgment

This research was supported by the theoretical and practical research topic of ideological and political education for college students in Guangxi in 2022 (2022SZ060).

8 References

[1] Lizunkov, V.G., Politsinskaya, E.V., Yagova, E.Y. (2021). Concept of preparing in-demand staff for the priority social and economic development areas in further education. International Journal of Engineering Pedagogy, 11(1): 95–105. https://doi.org/10.3991/ijep.v11i1.15013

[2] Hoda, N., Ahmad, N., Alqahtani, H., Naim, A. (2022). Social networking site usage, intensity and online social capital: A comparative study of LinkedIn and Facebook users with implications on technology-assisted learning. International Journal of Emerging Technologies in Learning, 17(9): 52–66. https://doi.org/10.3991/ijet.v17i09.29681

[3] Feng, L., Li, N., Huang, T., Bo, H. (2022). Social experience guidance for college students' entrepreneurship in the social network. International Journal of Emerging Technologies in Learning, 17(21): 197–213. https://doi.org/10.3991/ijet.v17i21.35115

[4] Zhang, H., Zhang, J., Shi, Y. (2022). A method to study group relationship of college students based on predictive social network. Scientific Programming, 2022: 5970188. https://doi.org/10.1155/2022/5970188

[5] Allen, R., Nakonechnyi, A., Seidmann, A., Roberts, J. (2020). Predicting students' college drop out and departure decisions by analyzing their campus-based social network text messages. In HICSS, 1–7. https://doi.org/10.24251/HICSS.2020.645

[6] Wang, Y., Sun, H. (2022). Behavior feature extraction method of college students' social network in sports field based on clustering algorithm. Journal of Intelligent Systems, 31(1): 477–488. https://doi.org/10.1515/jisys-2022-0030

[7] Chen, C., Chen, M. (2021). The research of social network analysis on college students' interactive relations. International Journal of Cognitive Informatics and Natural Intelligence (IJCINI), 15(2): 49–59. https://doi.org/10.4018/IJCINI.20210401.oa5

[8] McCall, T., Kim, H., Lee, E., Lakdawala, A., Bolton Iii, C.S. (2021). Content and social network analyses of depression-related tweets of African American college students. Communities & Collections. https://doi.org/10.24251/HICSS.2021.318

[9] Nie, M., Luo, W.M., Deng, H., Wang, W., Xia, H., Zhou, T. (2021). Research on the influence of college students' mental health on their social network structure. Journal of the University of Electronic Science and Technology of China, 50(2): 317–320. https://doi.org/10.12178/1001-0548.2020032

[10] Lattie, E.G., Kornfield, R., Ringland, K.E., Zhang, R., Winquist, N., Reddy, M. (2020). Designing mental health technologies that support the social ecosystem of college students. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, 1–15. https://doi.org/10.1145/3313831.3376362

[11] Zhang, R. (2017). The stress-buffering effect of self-disclosure on Facebook: An examination of stressful life events, social support, and mental health among college students. Computers in Human Behavior, 75: 527–537. https://doi.org/10.1016/j.chb.2017.05.043

[12] Tennant, J.E., Demaray, M.K., Coyle, S., Malecki, C.K. (2015). The dangers of the web: Cybervictimization, depression, and social support in college students. Computers in Human Behavior, 50: 348–357. https://doi.org/10.1016/j.chb.2015.04.014

[13] Bortolete, J.C., Bueno, L.F., Butkeraites, R., Chaves, A.A., Collaço, G., Magueta, M., Yanasse, H.H. (2022). A support tool for planning classrooms considering social distancing between students. Computational and Applied Mathematics, 41: 1–23. https://doi.org/10.1007/s40314-021-01718-w

[14] Zhang, H., Wang, X., Cui, Y., Zhao, T., Wang, J., Zuo, C. (2021). Research on the influencing factors to college students' learning burnout in online learning: Social support, learning pressure and autonomous learning ability. In 2021 International Symposium on Educational Technology (ISET), 79–83. https://doi.org/10.1109/ISET52350.2021.00026

[15] Barratt, J.M., Duran, F. (2021). Does psychological capital and social support impact engagement and burnout in online distance learning students? The Internet and Higher Education, 51: 100821. https://doi.org/10.1016/j.iheduc.2021.100821

[16] Gede Sudirtha, I., Wayan Widiana, I., Setemen, K., Sukerti, N.W., Widiartini, N.K., Santiyadnya, N. (2022). The impact of blended learning assisted with self-assessment toward learner autonomy and creative thinking skills. International Journal of Emerging Technologies in Learning, 17(6): 163–180. https://doi.org/10.3991/ijet.v17i06.29799

[17] Elshaiekh, N.E.M., Shehata, A.M.K., Elsawy, S. (2021). Learner autonomy in the digital environment of Omani higher education institutions: Sultan Qaboos university as a case study. In 2021 22nd International Arab Conference on Information Technology (ACIT), 1–9. https://doi.org/10.1109/ACIT53391.2021.9677206

[18] Watson-Brown, N., Scott-Parker, B., Senserrick, T. (2021). Higher order training supporting competence, autonomy, relatedness (HOT-CAR): A model to improve learner drivers' higher order skills. Transportation Research Part F: Traffic Psychology and Behaviour, 80: 79–89. https://doi.org/10.1016/j.trf.2021.03.013

[19] Artyushina, G.G., Zhurbenko, N.L., Sheypak, O. A. (2020). Principles of learner autonomy as a base for teaching professionally oriented foreign language. In Proceedings of the 2020 11th International Conference on E-Education, E-Business, E-Management, and E-Learning, 43–47. https://doi.org/10.1145/3377571.3379442

[20] Aryanti, N., Anggaira, A.S. (2020). Language learner autonomy: students' and teachers' reflection. In Proceedings of the 4th International Conference on Learning Innovation and Quality Education, 93: 1–6. https://doi.org/10.1145/3452144.3453837

[21] Fernández-Vera, F., Urrutia, D.C., Rossel, P.O., Herskovic, V., Fuentes, C. (2022). Social+Me: A persuasive application to increase communication between students and their support networks in Southern Chile. PEERJ Computer Science, 8: e848. https://doi.org/10.7717/peerj-cs.848

[22] Huang, Q. (2021). College English teachers' roles in fostering learner autonomy in the context of blended learning-an empirical research from the perspective of students based on SPSS 25.0. In 2021 2nd International Conference on Information Science and Education (ICISE-IE), 826–829. https://doi.org/10.1109/ICISE-IE53922.2021.00188

[23] Aziz, M.A.K., Dostal, J., Wang, M.X. (2020). The use of technology for promoting learner autonomy in English language classrooms. In 2020 18th International Conference on Emerging eLearning Technologies and Applications (ICETA), 22–26. https://doi.org/10.1109/ICETA51985.2020.9379164
[24] Duarte, M. (2018). Engineering students perceptions on learner autonomy a mixed methodology approach. In 2018 3rd International Conference of the Portuguese Society for Engineering Education (CISPEE), 1–6. https://doi.org/10.1109/CISPEE.2018.8593406

9 Authors

Runfang Duan is a lecturer in the Department of Student Affairs at Liuzhou Institute of Technology. She received her M.A. degree in education from Shanxi Medical University. Her research direction is college students' mental health education. Email: duanrunfang@163.com.

Xiaorui He is an associate professor in the Department of Student Affairs at Beijing College of Social Administration. She received her M.A. degree in education from Shandong Normal University. Her research direction is college students' mental health education. Email: hexiaorui@bcsa.edu.cn.

Article submitted 2023-02-07. Resubmitted 2022-04-05. Final acceptance 2023-04-11. Final version published as submitted by the authors.